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Investigation, Evaluation, and Dynamic Monitoring of Traditional Chinese Village Buildings Based on Unmanned Aerial Vehicle Images and Deep Learning Methods

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Abstract: The investigation, evaluation, and dynamic monitoring of traditional village buildings are crucial for the protection and inheritance of their architectural styles. This study takes traditional villages in Shandong Province, China, as an example, employing UAV images and deep learning technology. Utilizing the YOLOv8 instance segmentation model, it introduces three key features reflecting the condition of traditional village buildings: roof status, roof form, and courtyard vegetation coverage. By extracting feature data on the condition of traditional village buildings and constructing a transition matrix for building condition changes, combined with corresponding manual judgment assistance, the study classifies, counts, and visually outputs the conditions and changes of buildings. This approach enables the investigation, evaluation, and dynamic monitoring of traditional village buildings. The results show that deep learning technology significantly enhances the efficiency and accuracy of traditional village architectural investigation and evaluations, and it performs well in dynamic monitoring of building condition changes. The "UAV image + deep learning" technical system, with its simplicity, accuracy, efficiency, and low cost, can provide further data and technical support for the planning, protection supervision, and development strategy formulation of traditional Chinese villages.

Keywords: UAV images; deep learning; architectural feature recognition; dynamic monitoring; traditional Chinese village

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1. Introduction

1.1. Background

Traditional Chinese villages harbor a wealth of historical information and cultural landscapes. Spatial features serve as the spatial carriers that display and bear the historical and cultural characteristics of these villages. Protecting and inheriting the spatial features and the cultural factors they contain is essential to preserve the roots of culture and better achieve the synergy of conservation and development [1]. Architecture is the most direct reflection of the spatial features and regional characteristics of traditional villages and is also the spatial element that changes most rapidly and is most susceptible to external influences. Currently, the integrity and sustainability of architectural styles in traditional Chinese villages are prominent issues, mainly manifested in two aspects: first, a large number of traditional buildings suffer from continuous damage due to long-term vacancy and lack of maintenance; second, unorganized and unconstrained construction activities in villages cause constructive destruction to the architectural style. Investigating and evaluating traditional village buildings and dynamically monitoring changes are crucial prerequisites and means for the protection and inheritance of their architectural styles.

Current traditional methods of building investigation, evaluation, and dynamic monitoring rely heavily on manual labor, which not only consumes a significant amount of time and economic costs but also has considerable issues with data accuracy and the continuity of monitoring. How to improve the timeliness of traditional village building information acquisition and reduce costs to achieve continuous, dynamic, and real-time assessment and change monitoring is a question worth exploring.

With technological advancements, artificial intelligence is increasingly applied to the field of cultural heritage protection. Image recognition technology based on deep learning provides an effective method for identifying and extracting spatial features of traditional villages [2,3]. On one hand, data mining, identifying, and extracting traditional village spatial feature information that does not rely on subjective judgment, and analyzing the underlying patterns behind the spatial forms of traditional villages, can provide scientific data support for their protection. On the other hand, convenient long-term acquisition of spatial feature data can provide an effective means for monitoring traditional village protection activities and construction behaviors.

This study, combined with the practice of traditional village protection and utilization, takes unmanned aerial vehicle (UAV) images as the data foundation and applies deep learning technology to the identification of traditional village architectural features. Through deep learning model training, it extracts key feature information that reflects the condition of traditional village buildings, constructing an efficient, low-cost technical method for the investigation, evaluation, and dynamic monitoring of traditional village buildings, further enriching and deepening the connotation of research on traditional Chinese villages.

1.2. Related Work

The architectural investigation, evaluation, and change monitoring of traditional villages involve assessing the condition of buildings and capturing their changes through continuous observation to determine the extent of these changes and their impact on the protection and development of traditional villages. Western countries began attempting to monitor and plan for the protection of cultural heritage in the 1970s [4], while China only started incorporating construction development monitoring into urban planning and design information systems at the beginning of the 21st century [5]. With the application of digital technology in urban construction [6], heritage conservation [7], monitoring, and early warning [8], digital monitoring has become a major focus in research and practice. Current research primarily uses high-resolution remote sensing satellite images [9], terrestrial 3D laser scanning [10], digital low-altitude photogrammetry [11], and UAV sensors [12]; it is applied in fields such as national spatial development and ecological protection [13], cultural heritage site conservation [14], resource and environmental carrying capacity assessment [15], structural safety monitoring of architectural heritage [16], and disaster prevention [17]. Currently, there is a scarcity of research in China specifically dedicated to the spatial survey, evaluation, and change monitoring of traditional villages. The existing studies on the spatial survey and evaluation of traditional villages predominantly focus on cultural landscapes [18], heritage resources [19], and specific landscape elements such as soundscapes [20] and color landscapes [21]. These studies typically employ traditional techniques and methods, including survey statistics, spatial syntax, and topological analysis, which are deficient in providing a systematic and quantitative analysis of traditional village spaces using modern tools. The monitoring research is even more limited, with the few available research outcomes concentrating on the monitoring and early warning of the impact of tourism development on the protection of traditional village spaces [22] and the construction of monitoring and early warning systems for traditional villages [23,24]. The field of dynamic monitoring research aimed at the protection and development of traditional villages still lacks a novel holistic perspective and intelligent technologies.

The application of deep learning technology in the protection of traditional villages is becoming increasingly widespread, with researchers conducting in-depth studies on the classification of traditional village landscapes [25], landscape evaluation [26], spatial texture recognition [27], and classification and quantification of residential buildings [28]. Current research on the identification of architectural features in traditional Chinese villages mainly focuses on three aspects: First, the optimization of deep learning algorithm models and the improvement of recognition accuracy. Hang Xue et al. [29] introduced a multi-scale fusion and detail enhancement network MAD-UNet for the effective extraction of rural buildings. Feng Fan et al. [30] enhanced the extraction capability of multi-scale buildings based on a multi-input multi-output and multi-feature fusion fully convolutional network. Chen Xuejiao et al. [31] studied methods for extracting buildings from high-resolution remote sensing images using a densely connected feature pyramid fusion network. By continuously optimizing algorithm models, the accuracy and efficiency of building identification are improved. Second, research on the selection of extracted features explores common architectural feature recognition indicators, including color [32], spectrum [33], texture [34], shape [35], shadow [36], and semantics, designing effective recognition feature systems to better describe buildings. Third, the specific application of semantic segmentation and instance segmentation algorithms is explored, with studies investigating the extraction of buildings from remote sensing and UAV images using improved U-NET [37], HF-FCN [38], Mask R-CNN [39], and Mask Scoring R-CNN [40] semantic segmentation and instance segmentation algorithm models, with instance segmentation algorithm models showing better applicability for the identification of buildings in rural areas.

Deep learning, with its capacity for leveraging vast amounts of data and computational power, has demonstrated significant technological advantages. Utilizing high-resolution satellite remote sensing imagery and UAV imagery, deep learning techniques have been employed by researchers for extensive studies on rapid detection of urban building targets [41], precise identification and extraction of buildings [42], automatic recognition of urban unauthorized constructions [43], post-earthquake damage identification of buildings [44,45], structural classification of buildings [46], and analysis of architectural features [47]. On this basis, researchers have also explored the application of deep learning technology in the field of urban community spatial planning [48], establishing it as a vital technical instrument and research direction in urban and rural spatial planning. Conversely, the application of deep learning technology in the domain of traditional Chinese villages remains relatively scarce, with only preliminary discussions on the intelligent recognition of rural buildings [49] and the automatic classification of rural architectural features [50]. Research on the identification of spatial characteristics and dynamic monitoring of traditional villages is essentially non-existent. Given the vast number of traditional Chinese villages and the urgent tasks of protection and development they face, it is imperative to undertake adaptive and innovative explorations based on existing research and practices. This study focuses on the application pathways of deep learning in the protection and development of traditional Chinese villages, aiming to further expand the practical application domains of deep learning.

1.3. Characteristics for Architectural Condition Recognition and Assessment

From the perspective of image recognition, the identification of architectural features based on UAV orthoimages primarily encompasses three aspects: the condition of building roofs (intact and damaged), roof forms, and the coverage status of courtyard vegetation [51]. Through summarization and refinement, in the traditional villages of the Shandong region, the forms of building roofs are categorized into two major types: double-sloped roofs and flat roofs. The double-sloped roofs can be further refined into three subtypes: red tile, gray tile, and colored steel tile (as shown in Figure 1). Additionally, influenced by traditional concepts such as Feng Shui, evergreen coniferous species are rarely planted in rural courtyards in the Shandong region, with a preference for more practical fruit trees. The courtyard vegetation exhibits distinct coverage characteristics during the growing season. Based on the aforementioned classification criteria, the building conditions can be further divided into six image recognition features, which serve as the basis for deep learning-based image recognition (see the category division in Figure 2).

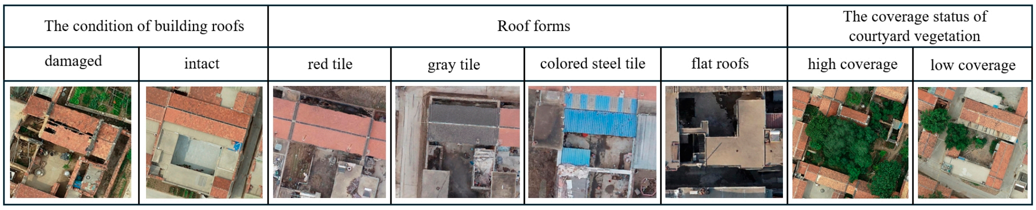

Figure 1. Examples of architectural roof features and courtyard vegetation coverage features.

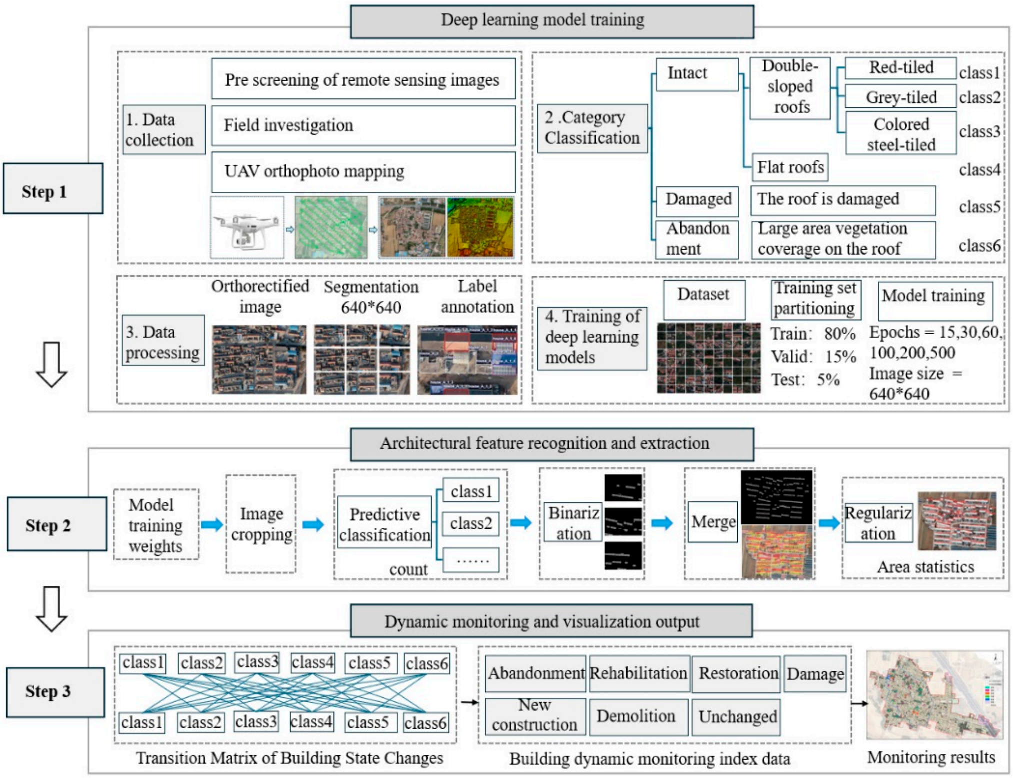

Figure 2. Technical flowchart.

1.4. Dynamic Monitoring of Building Conditions and Assessment Criteria

Through extensive field research combined with relevant literature [52,53] and protection and utilization requirements [54,55], the conditions and changes of traditional village buildings primarily include forms such as abandonment, damage, restoration, rehabilitation, new construction, demolition, and remaining unchanged. These forms constitute the main content of the dynamic monitoring of changes in the conditions of traditional village buildings. Based on the summary of research data from traditional villages in Shandong Province, the aforementioned monitoring content can be discerned through the changes in roof condition, roof form and color, courtyard vegetation coverage, and their interconversion relationships.

The characteristics and criteria for distinguishing the changes in the conditions of traditional village buildings are as follows:

- Abandonment: The residential status shifts from occupied to unoccupied. This can be identified by observing the condition of courtyard vegetation and its changes; unoccupied courtyards exhibit irregular, large areas covered with weeds and vines.
- Damage: Mainly manifested by partial or complete destruction of the roof, which can be identified by changes in the roof's condition.
- Restoration: Undertaken to preserve the existing condition of a building or to appropriately restore it to its original state, this involves repair, reinforcement, maintenance, and improvement works with an emphasis on maintaining and restoring the building's

original appearance and historical characteristics. In traditional village architecture, restoration focuses on reviving the traditional materials and styles of the building's roof and facade. Therefore, it can be identified through observations of changes in the roof's condition, form, and color.

- Rehabilitation: Conducted to enable a building to be reused or to exhibit its original functions and value, this work emphasizes the restoration of the building's original functionality and utility. Traditional building materials and styles may not be used. It can be identified through observations of changes in the roof's condition, form, and color.
- New construction: Construction activities on vacant land during the monitoring period, which can be identified by the emergence of a roof where there was none before.
- Demolition: The removal of existing buildings to create vacant land, which can be identified by the disappearance of a roof where there was one before.
- Unchanged: Well-preserved buildings that have not undergone significant changes in their condition during the monitoring period, which can be identified by the stability of the roof's condition.

2. Materials and Methods

The overall workflow and main procedures are illustrated in Figure 2. It contains three major steps: deep learning model training, architectural feature recognition and extraction, and dynamic monitoring and visualization output.

Initially, fundamental data was amassed via remote sensing images, field investigations, and UAV images, followed by the development of deep learning models. Subsequently, these models were deployed to identify and extract architectural features from the sample villages, leveraging image feature extraction to inform subsequent dynamic monitoring. Utilizing the extracted data, in conjunction with manual discrimination, the state of buildings and their transformations were categorized, statistically analyzed, and visually presented, facilitating the assessment and dynamic monitoring of traditional village buildings.

2.1. Study Area and Data Collection

2.1.1. Study Area

The construction of deep learning model data in this study took traditional villages in Shandong Province, China, as samples. Shandong Province currently boasts 168 traditional Chinese villages. The geographical features of the coexistence of land and sea, as well as the rich terrain and landforms in Shandong Province, and the profound cultural heritage formed by the integration of diverse cultures, such as Qilu culture and marine culture, have nurtured traditional villages with diverse types and distinct regional characteristics. These villages are categorized into five spatial typologies: the Eastern Shandong Peninsula, Central Shandong Mountainous Region, Southern Shandong Hills, Southwest Shandong Plain, and Northern Shandong Plain, making the province a significant distribution area and typical examples of traditional Chinese villages.

2.1.2. UAV Photography

UAV images offer a higher planar data acquisition rate for upper areas such as building roofs, enabling the collection of multi-directional data information, and serving as an effective method for the investigation, evaluation, and change monitoring of traditional village architecture. The research team conducted field investigations of traditional villages within the jurisdiction of Shandong Province. Considering the limitations of the accuracy of remotely sensed images available to the public and the complexity of the traditional village architectural environment, this study utilized UAV photography to obtain orthoimages of 168 traditional Chinese villages. These images are used as the data source for the training set of the deep learning model, and the image data acquisition process is depicted in Figure 3.

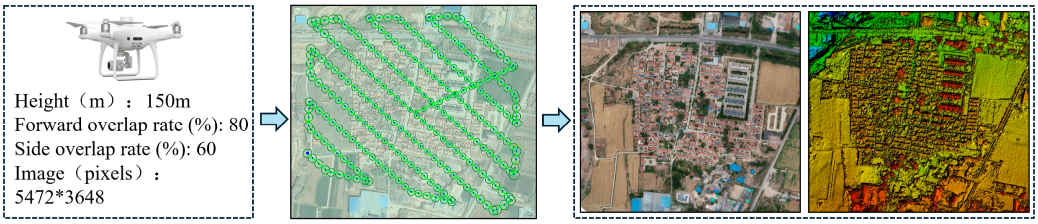

Figure 3. Description of the UAV photography.

2.2. Deep Learning-Based Feature Extraction Model

2.2.1. Building Feature Extraction by YOLOv8

Currently, deep learning models applied to image recognition are primarily divided into two major categories: one-stage algorithm models represented by YOLO [56] and SSD [57], and two-stage algorithm models represented by Mask R-CNN [58] and Faster R-CNN [59]. Compared to two-stage algorithm models, one-stage algorithm models can directly classify samples without the need for generating region proposal boxes, obtaining recognition results in a single phase, thus demonstrating superior advantages in terms of speed and efficiency.

Among the one-stage algorithm models, the YOLO series is a typical example. With the algorithm optimization of the YOLOv8 model [60], particularly in processing speed and data capacity, it has shown excellent performance in building image analysis tasks. In the preliminary model selection phase of this study, for the recognition of rural building features, YOLOv8 demonstrated good reliability and accuracy; therefore, this study adopts the instance segmentation model of YOLOv8 as the basic model for the study.

YOLOv8 is a version within the object detection and image segmentation series models developed by Ultralytics. YOLOv8 enhances the network's gradient flow by introducing the C2f module in place of the traditional C3 structure [61]. It incorporates the Mosaic technique during the data augmentation phase to enrich the diversity of image backgrounds and simultaneously turns off this enhancement during the later stages of training to stabilize model convergence [62], thereby improving the model's learning capabilities. In terms of loss functions, YOLOv8′s detection head employs CIoU and DFL, while the classification head uses the binary cross-entropy (BCE) loss function, further enhancing the model's performance [63]. To accommodate varying data capacity requirements, YOLOv8 fine-tunes the model's channel configuration, offering five different versions: n, s, m, l, and x [64]. Considering the data set capacity of this study, YOLOv8n was selected as the specific model for research.

This study utilized the YOLOv8n instance segmentation model, based on the high-resolution UAV orthoimagery obtained, and through the comparison of multi-period image data recognition results, combined with manual assistance, to determine the changes in the state of buildings, identify the impacts of these changes, and accordingly conduct investigations, evaluations, and dynamic monitoring of traditional village buildings.

2.2.2. Data Preprocess

To meet the requirements for sample size and image resolution during the training phase of the YOLOv8 model, the output accuracy of the collected orthoimages was set to 10 cm. Subsequently, the original orthoimagery was cropped into 640*640 pixel images and different types of buildings and courtyards in the orthoimages were semantically segmented and annotated using the labeling software Labelme 2014 (Figure 4).

To achieve image enhancement and expansion of the training dataset, avoid unnecessary loss of image resolution during processing, and enhance the model's generalization ability, the following data augmentation measures were taken: First, horizontal flipping was performed on each input image (Figure 5a); Second, random rotation was applied to the images (Figure 5b), with the angle varying between −15° and +15° to reflect the possible orientations of buildings in actual scenes; Third, blur effects were introduced (Figure 5c), with a maximum blur radius of 2.5 pixels, to mimic image blur caused by camera shake or rapid movement. Through the enhancement of the sample dataset, an average of three variants was generated for each original image, expanding the scale of the training set and improving the quality of the model's training dataset through augmentation measures.

Figure 4. Example of original orthoimage cropping.

Figure 5. Data augmentation measures example (**a**). Image flipping, (**b**). Image rotation, (**c**). Image blurring).

2.2.3. Model Training and Evaluation

This study employed the YOLOv8n-seg.pt model for instance segmentation of buildings and courtyards in orthoimagery, utilizing the deep learning framework of PyTorch 1.1.2, coupled with CUDA 11.7 for GPU-accelerated optimization during model training. To ensure the quality of input data, the image size was uniformly set to 640*640 pixels during training, and the training epochs were set to 15, 30, 60, 100, 200, and 500 epochs to thoroughly train the model and achieve stable performance.

To assess the model's stability, three performance metrics are introduced: Precision, Recall, and Mean Average Precision (Table 1). Precision is used to evaluate the proportion of correctly predicted positive samples by the model; Recall is used to assess the proportion of all true positive samples that the model can identify; Mean Average Precision represents the average accuracy of predictions across multiple classes, used to evaluate the quality of the model's algorithm. It can be divided into two metrics, mAP50 and mAP50-95. The mAP50 metric indicates the average precision at a 50% Intersection over Union (IoU) threshold, which is the ratio of the intersection area to the union area between the predicted region and the true region. The mAP50-95 metric indicates the average precision across the 50–95% IoU threshold range.

Table 1. Model stability evaluation metrics.

Metrics		Formula
Precision		$\frac{TP^*}{TP+FP^*}$
Recall		$\frac{TP}{TP+FN^*}$
Mean Average Precision	mAP50	the mAP value at the 50% IoU * threshold
	mAP50-90	the mAP value within the 50–95% IoU threshold range

* *TP*: Number of buildings correctly classified; *FP*: Number of buildings incorrectly classified as this category (i.e., buildings of other categories incorrectly identified as this category); *FN*: Number of buildings that should have been identified as this category but were not; IoU threshold represents the ratio of the intersection area to the union area between the predicted region and the true region.

Following the training process described previously, and in conjunction with the comparison of the loss function across different training epochs (Figure 6), it can be observed that after 30 epochs, the loss function metric becomes stable, indicating effective model fitting. After 100 training epochs, the model reaches a plateau, and continued training leads to a decrease in overall accuracy due to overfitting. A comprehensive evaluation indicates that the training effect at the 60th epoch is superior to other batches, with the precision of detection boxes and instance segmentation on the training set stabilizing at 94.6% (Table 2), representing the optimal performance. Therefore, the training results from 60 epochs are selected as the predictive weights for the model. Concurrently, to enhance understanding of the model's recognition process and for further analysis, the prediction results are visually processed. Figure 7 illustrates the visualization starting from the original.

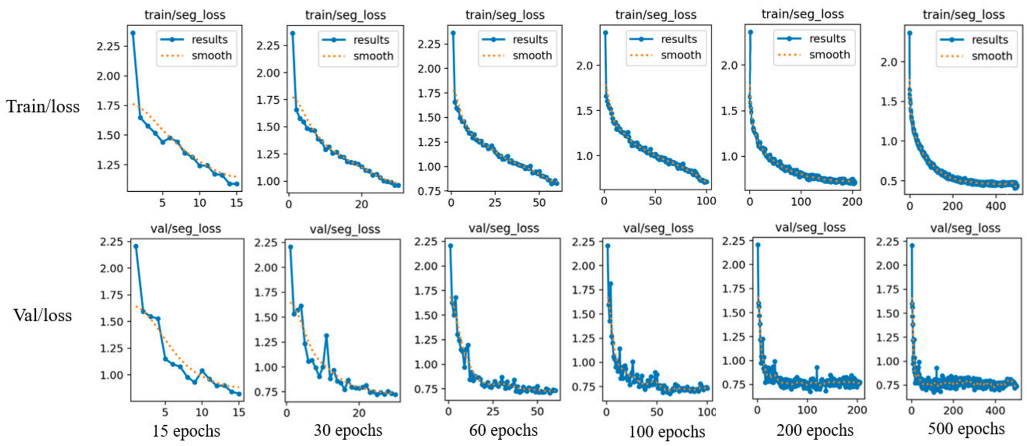

Figure 6. Loss function across different epochs.

Table 2. Training results across different training epochs.

Epochs	Box				Mask			
	Precision	Recall	mAP50	mAP50-95	Precision	Recall	mAP50	mAP50-95
15	0.873	0.756	0.834	0.686	0.873	0.756	0.829	0.656
30	0.908	0.740	0.840	0.690	0.908	0.740	0.842	0.609
60	0.946	0.735	0.841	0.694	0.946	0.825	0.830	0.658
100	0.931	0.740	0.833	0.697	0.931	0.790	0.834	0.678
200	0.870	0.768	0.801	0.672	0.916	0.730	0.798	0.629
500	0.871	0.805	0.836	0.695	0.895	0.790	0.841	0.675

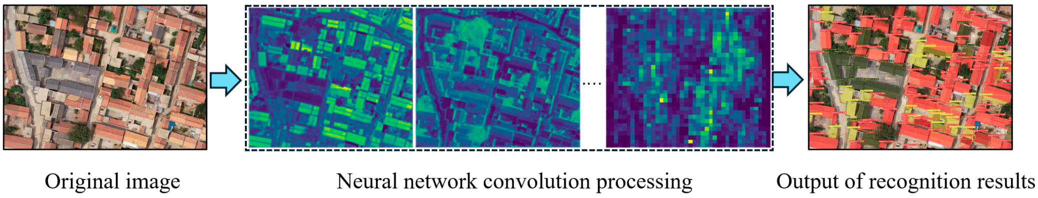

Figure 7. Visualization process in deep learning.

2.3. Model Transferability

To assess the transferability of the trained model, this study selected 24 typical villages from five traditional village spatial style areas in Shandong Province as test samples, referring to the style types and regional divisions of traditional villages in Shandong [65]. The selection of test sample villages took into account factors such as style features, village area, settlement morphology, preservation status, altitude, topography, and landforms, ensuring that the test samples cover all types of architectural characteristics of traditional villages in Shandong Province. A total of 57,738 validation data points were obtained (Figure 8). The test results were compared with actual data, as shown in Table 3. The model achieved high recognition accuracy for damaged buildings, flat-roofed buildings, red-tiled roof buildings, and gray-tiled roof buildings, all above 95%, with the recognition accuracy for red-tiled roof buildings reaching 97.1%. The recognition accuracy for abandoned buildings and buildings with colored steel tile roofs was relatively lower; the accuracy for abandoned buildings was 91.3%, mainly because the primary identification feature for abandoned buildings is the vegetation coverage in the courtyards, which can be easily misidentified due to the large area and high density of vegetation in public spaces and green areas within the villages. The recognition accuracy for buildings with colored steel tile roofs was 86.7%. Combining field research, the relatively low accuracy is attributed to some colored steel tiles exhibiting features similar to red tiles due to rust. On the other hand, some buildings have adopted colored steel tiles that imitate the gray roof style to protect the traditional village appearance, which also increases the difficulty of identification. Considering the limitations of the actual collected data and the diversity of architectural characteristics in traditional villages, the trained model demonstrates high accuracy in identifying key features such as roofs and courtyard vegetation coverage, meeting the requirements for practical work such as the investigation, evaluation, and dynamic monitoring of changes in traditional village buildings within the Shandong Province.

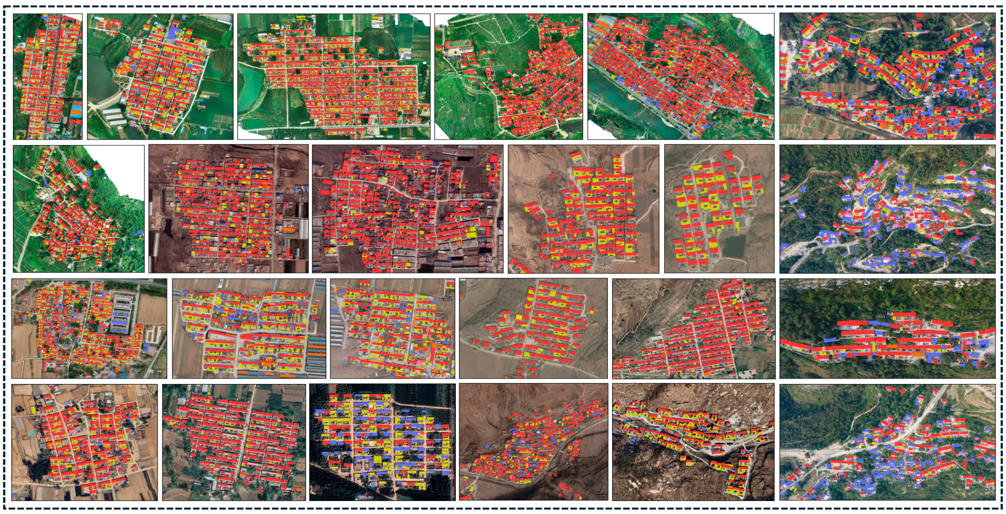

Figure 8. Test sample villages building feature recognition example.

Table 3. Test sample villages building feature recognition results.

Classification	Original Quantity	Identify Quantity	Correct Classification	Unrecognized	Identify Errors	Precision	Recall
Abandonment	552	579	528	24	51	91.3%	95.7%
Damage	408	394	377	31	17	95.6%	92.4%
Red-tiled	25340	25940	25187	153	753	97.1%	99.4%
Gray-tiled	4230	4278	4111	119	167	96.1%	97.2
Colored steel-tiled	3608	3524	3056	552	468	86.7%	84.7%
Flat roof	23600	24343	23199	401	1144	95.3%	98.3%

3. Results

This study selects Dongfanliu Village in Zhangqiu District, Jinan City, Shandong Province as the sample village for model application (Figure 9). Dongfanliu Village is a traditional Chinese village and a famous historical and cultural village in Shandong Province, with complete preservation of the spatial pattern and traditional architectural forms, making it a typical example of traditional villages in the central Shandong region [66]. In 2022, Dongfanliu Village was included in the national demonstration of concentrated protection and utilization of traditional villages. The construction of the demonstration zone has led to overall protection and enhancement of the traditional village. Concurrently, the construction of the Jiwei Expressway, which started in the same period, passes through the northern part of the village. These protective and constructive actions have had certain impacts on the village's architectural style and spatial texture. The significant spatial changes in Dongfanliu Village provide an excellent sample for architectural investigation evaluation and dynamic monitoring. The research team conducted field investigation in Dongfanliu Village in June 2020 and June 2024, and obtained orthoimages of the village using unmanned aerial vehicles (Figure 10).

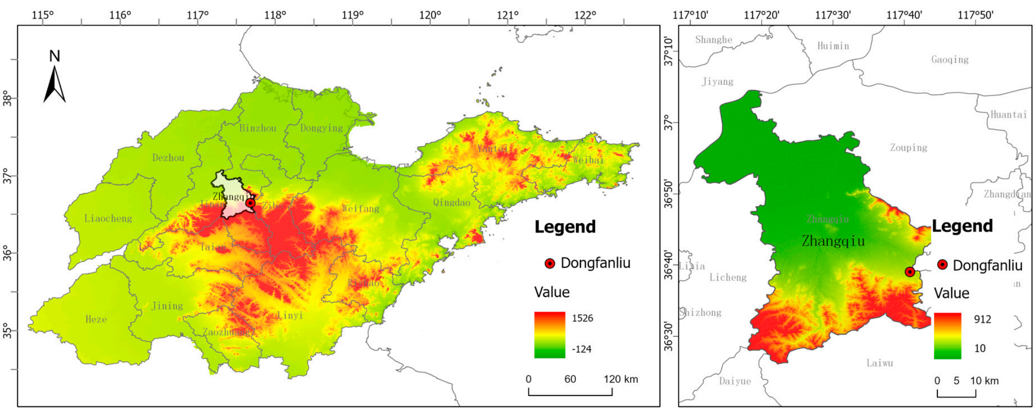

Figure 9. Location map of Dongfanliu village.

Figure 10. UAV orthoimagery of Dongfanliu village (**a**) captured in June 2020, (**b**) captured in June 2024.

3.1. Building Condition Assessment

3.1.1. UAV Image Recognition

Inputting the UAV images from 2020 and 2024 into the deep learning model, this study extracts the building condition features from the two periods of village images (Figures 11 and 12) and compares the changes in the data between the two periods. The results (Table 4) indicate that compared to 2020, in 2024, the number of damaged buildings in the village decreased from 31 to 15; the number of abandoned buildings decreased from 30 to 26; the number of red tile roofs decreased from 1343 to 1297; the number of gray tile roofs increased from 17 to 36; the number of colored steel tile roofs decreased from 44 to 24; and the number of flat-roofed buildings decreased from 1222 to 1200.

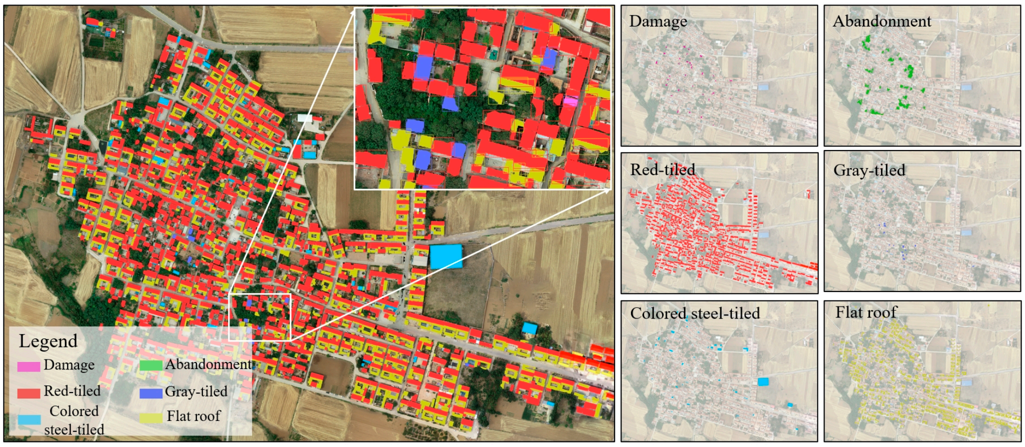

Figure 11. Building condition recognition results of Dongfanliu village in 2020.

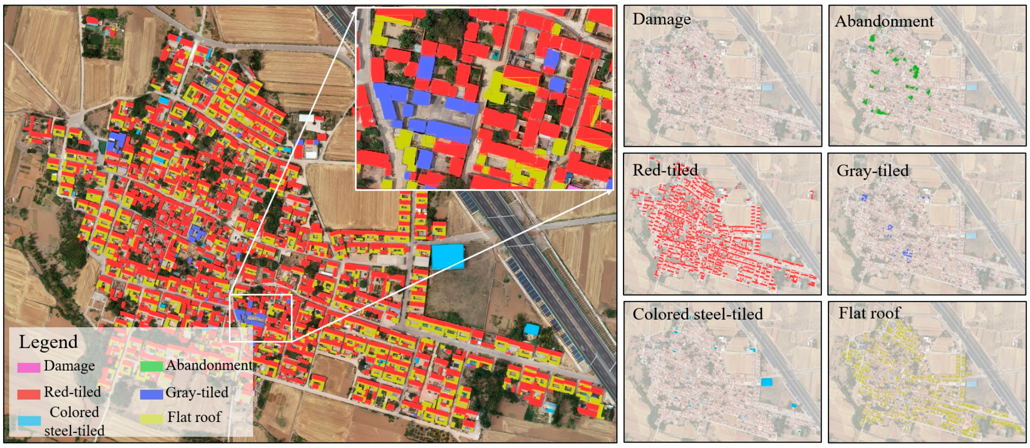

Figure 12. Building condition recognition results of Dongfanliu village in 2024.

Table 4. Analysis of changes in building condition recognition results between 2020 and 2024 in Dongfanliu village.

Classification	2020	2024	Change Quantity
Abandonment	30	26	4
Damage	31	15	16
Red-tiled	1343	1297	46
Gray-tiled	17	38	19
Colored steel-tiled	44	24	20
Flat roof	1222	1200	22

3.1.2. Changes in Building Condition

Based on the extracted data, a differential analysis was conducted on the building condition patches from the two periods (Figure 13). By combining manual discrimination to eliminate recognition errors, a transition matrix of building condition changes was constructed (Table 5), which analyzes the interconversion relationships between different types of building conditions. Specifically, four abandoned buildings were transformed into gray-tiled buildings; seven damaged buildings were changed into red-tiled buildings, and nine into gray-tiled buildings; five red-tiled buildings were converted into gray-tiled buildings, and 27 were demolished; 12 colored steel tile-roofed buildings were demolished, and four were changed into red-tiled buildings; 30 flat-roofed buildings were demolished; and three new gray-tiled buildings were constructed.

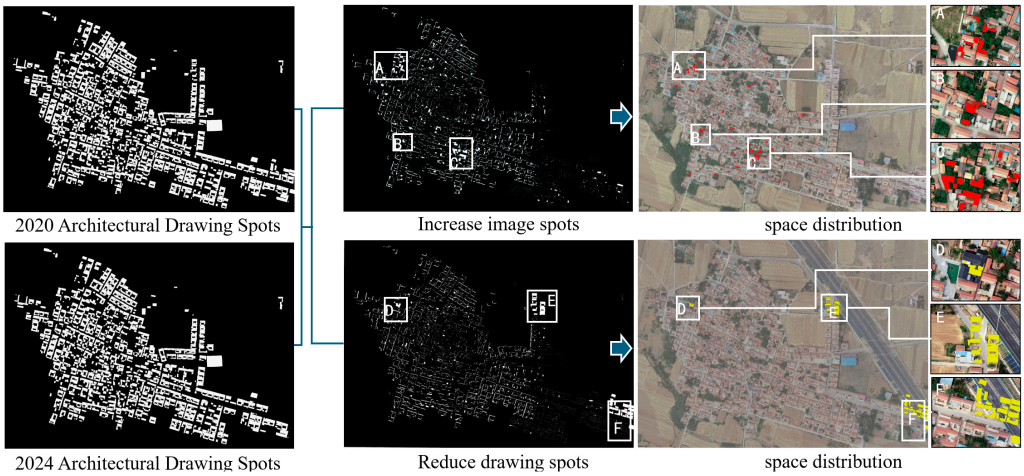

Figure 13. Building patch change analysis from 2020 to 2024.

Table 5. Transition matrix of building condition changes from 2020 to 2024.

2020	2024								
	Abandonment	Damage	Red-Tiled	Gray-Tiled	Colored Steel-Tiled	Flat Roof	Demolition	Redundancy	Total Quantity
Abandonment	26	0	0	4	0	0	0	0	30
Damage	0	15	7	9	0	0	0	0	31
Red-tiled	0	0	1286	5	0	0	27	15	1343
Gray-tiled	0	0	0	17	0	0	0	0	17
Colored steel-tiled	0	0	4	0	24	0	12	4	44
Flat roof	0	0	0	0	0	1200	30	−8	1222
New construction	——	0	0	3	0	0	——	——	3
Total quantity	26	15	1297	38	24	1200	69	11	——

3.2. Building Condition Dynamic Monitoring

In accordance with the definitions of traditional village building conditions and their forms of change, as described earlier, the data from the building condition change transition matrix were further transformed and categorized into types such as abandonment, damage, restoration, rehabilitation, new construction, demolition, and remaining unchanged, to obtain dynamic monitoring indicator data for building condition changes (Table 6). Specifically, there were 18 restored buildings, including the restoration of nine originally damaged buildings, four originally abandoned buildings, and the traditional-style restoration of five originally red-tiled buildings; 11 rehabilitated buildings, comprising the rehabilitation of seven damaged buildings and four colored steel tile-roofed buildings; three newly built traditional-style buildings; 69 demolished buildings, all of which were of modern style; and 2527 unchanged buildings. The dynamic monitoring results of building condition changes from 2020 to 2024 are shown in Figure 14.

Table 6. Dynamic monitoring indicator data of building condition changes from 2020 to 2024.

	Abandonment	Damage	Restoration	Rehabilitation	New Construction	Demolition	Unchanged
2020	30	31	——	——	——	——	——
2024	26	15	18	11	3	69	2527
Quantity changes	−4	−16	18	11	3	69	2527

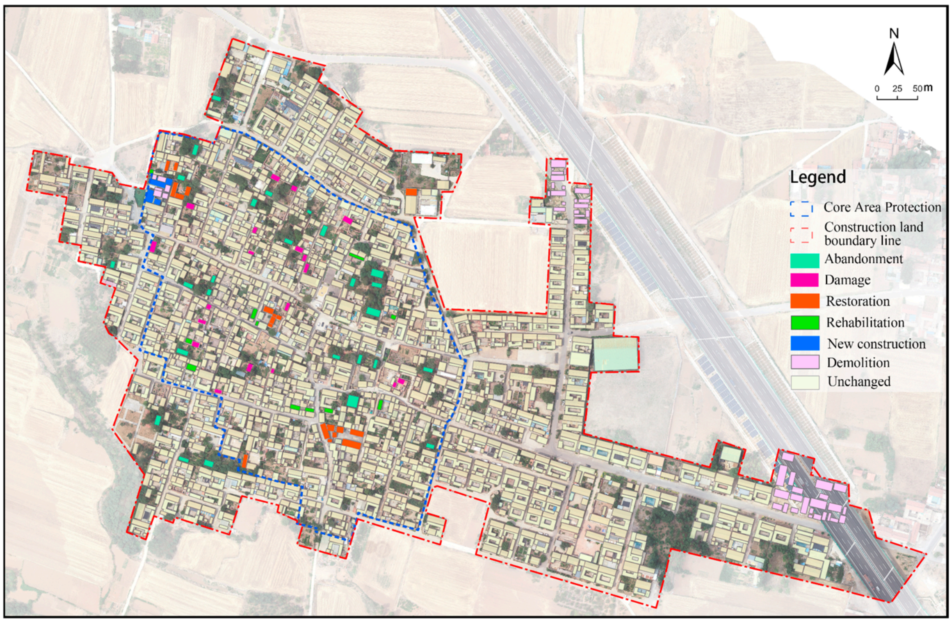

Figure 14. Dynamic monitoring results of building condition changes from 2020 to 2024.

In conjunction with the "Conservation and Development Plan for Dongfanliu Traditional Village," restoration, rehabilitation, and newly built traditional-style buildings are all located within the core protection area of the traditional village. The restored buildings are mainly in the southern part of the village, representing the restoration and protection of the Taihe Hall traditional residential building complex, which has formed a more complete historical building cluster in the area through restoration. The rehabilitated buildings are primarily concentrated in the central part of the village, including the rehabilitation of the Gong Family Ancestral Hall and the former residence of the martial scholar, which has provided better protection for key historical buildings in the village and further enriched the traditional village's architectural style. The restoration and rehabilitation of buildings reflect the positive effects of the concentrated protection and utilization of traditional villages carried out in 2022.

Newly built buildings are mainly located in the northwest of the village, where some original modern buildings have been demolished to make way for new traditional-style constructions, demonstrating the strict control of construction activities in the core protection area as stipulated by the conservation and development plan, which has been well implemented. Demolished buildings are concentrated in the eastern part of the village, all within the construction control zone designated by the traditional village conservation and development plan, mainly due to the occupation of the village by a newly built expressway. The construction of the expressway has significantly impacted the integrity of the village's spatial pattern and the completeness of its style. In the construction of major infrastructure projects, it is necessary to enhance the awareness of protecting traditional villages and strengthen the scientific demonstration of site (route) selection to reduce the disturbance and impact on cultural heritage resources such as traditional villages.

4. Discussion

4.1. Enhancing the Work Efficiency and Precision of Traditional Village Architecture Investigation and Evaluation

Architectural investigation and evaluation are essential for the protection and inheritance of traditional village architectural styles. Currently, traditional methods of architectural investigation and evaluation rely heavily on field investigations, which involve conducting individual research on village buildings to obtain relevant information. These conventional approaches are time-consuming, costly, labor-intensive, and subject to human error, which affects the accuracy and efficiency of the research. In contrast, this study proposes a cost-effective solution that combines UAV images with deep learning technology for the investigation and evaluation of traditional village architecture. According to traditional research methods, a team of six people spends a total of 20 h conducting field investigations and feature labeling for 2556 buildings in a single case study village, and an additional five hours on data analysis and visualization. The same village's UAV image collection and processing can be completed by one person in 90 min (including 30 min for UAV outdoor flight preparation and aerial photography, and 60 min for UAV orthoimage output). With a well-trained deep learning model, pre-processing of UAV aerial data, architectural feature recognition, data statistics, and visualization image output can be completed within 90 min (Figure 15). In terms of the overall time consumption, the former is 50 times longer than the latter, and with the expansion of the research area and the increase in the number of case study villages, the new method proposed in this study can significantly improve work efficiency. Moreover, the architectural feature recognition method and judgment dimensions proposed in this study, which mainly focus on the status of building roofs, roof forms, and courtyard vegetation coverage, have few indicators and high recognition accuracy. In the verification of traditional village architectural features in Shandong Province, the overall model recognition accuracy reached 95.3%, meeting the requirements for the actual work of traditional village architectural investigation and evaluation and change monitoring. Its advantages of being fast, accurate, and low-cost make it suitable for large-scale traditional village research.

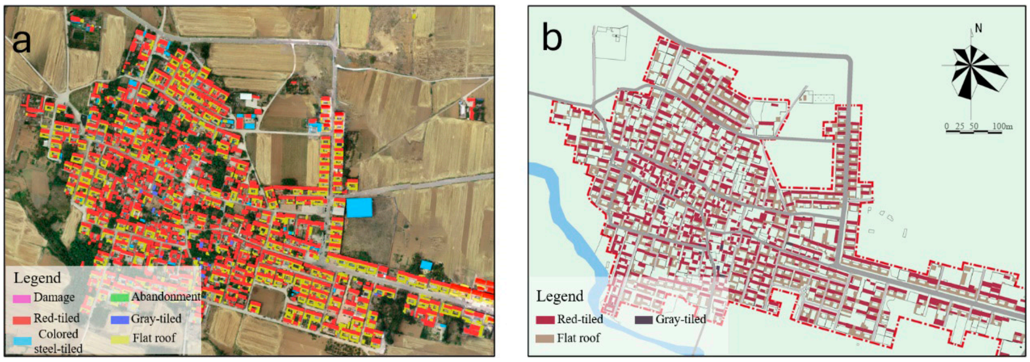

Figure 15. Comparison of deep learning model recognition results (**a**) with manual annotation results (**b**).

4.2. The Potential for Diversified Applications in the Conservation and Development of Traditional Villages

This study achieves the investigation, evaluation, and dynamic monitoring of changes in traditional village architecture through the transformation and classification of architectural feature recognition and feature change transition matrices, with the results visualized for spatial analysis. Taking Dongfanliu Village as an example, abandoned and damaged buildings are mainly distributed within the core protection area, showing a generally scattered and locally concentrated pattern, which is extensive and requires enhanced protective measures. Between 2020 and 2024, buildings that were repaired and renovated were relatively concentrated, all located at significant spatial nodes of the village, positively contributing to the protection of the village's spatial structure and texture. During the same period, demolished buildings were concentrated in the eastern part of the village, primarily due to the construction of a highway affecting the village. By analyzing the spatial distribution and change characteristics, long-term, dynamic, and precise monitoring of traditional villages can be realized.

Additionally, the technical methods proposed in this study have broad application prospects in other aspects of the protection and development of traditional villages. For instance, by analyzing the extracted architectural feature data, it is possible to accurately identify whether buildings are inhabited or uninhabited and assess the state of building abandonment without the need for field research. Furthermore, rapid quantitative assessment of damage and abandonment in the core protection areas of traditional villages can be conducted, which not only helps to accurately identify the protection status of traditional villages but also determines key protective spaces and directions. By analyzing the spatial distribution of historical and characteristic buildings in the village, detailed data support can also be provided for the optimization of traditional village spatial patterns and the direction of architectural renewal.

4.3. Limitations and Further Research Directions

This study innovatively applies deep learning technology for the investigation, evaluation, and dynamic monitoring of changes in traditional village architecture, but it also has certain limitations. Although UAVs can conveniently obtain image data, the collected samples are limited. In the future, it may be possible to supplement the data by acquiring high-precision remote-sensing satellite images or commercial UAV images. Moreover, this study uses traditional villages within Shandong Province as samples, but the spatial characteristics of traditional villages in China vary greatly by region. To enhance the applicability of the model, it is necessary to collect spatial feature information from traditional villages in different regions of China, expand the sample training set data, and broaden the scope of the model application. Due to the consideration of obtaining courtyard vegetation coverage features, the data collected are mostly from summer images. Further refinement of recognition features and enhancement of the model's accuracy and reliability are still needed for identifying the characteristics of traditional village architecture in other seasons, especially in northern regions.

The study primarily employs the YOLOv8 instance segmentation model to recognize the architectural features of traditional villages, with research results focusing on the statistics of the number of buildings with different features and their changes. This technical method still has significant potential for expansion in the automated extraction of other spatial feature data. It can be combined with related analysis software such as ArcGIS Pro 3 to obtain specific spatial data, including building area, building spacing, building orientation, building density, settlement morphology and boundary shape, and distribution of public spaces. By extracting various types of spatial parameters, it can provide data support for the research and practice of traditional village conservation.

5. Conclusions

This study utilizes UAV image and deep learning technology to explore a new technical approach and workflow for the investigation, evaluation, and dynamic monitoring of traditional village architecture. By employing the YOLOv8 instance segmentation model and incorporating three key features reflecting the condition of traditional village architecture—namely, the state of building roofs, roof forms, and the coverage of courtyard vegetation—the study extracts feature data of traditional village buildings, constructs a matrix of building condition changes, and combines manual judgment assistance to classify, count, and visually output the conditions and changes of buildings, achieving investigation, evaluation, and dynamic monitoring of traditional village architecture. The results indicate that deep learning technology can significantly enhance the efficiency and accuracy of the investigation and evaluation of traditional village architecture and has a good application effect in the dynamic monitoring of the condition of traditional village buildings. The "UAV image + deep learning" technical system, with its simplicity, accuracy, efficiency, and low cost, can provide timely and reliable data and technical support for the planning, protection supervision, and development strategy formulation of traditional villages. As the model dataset expands and the algorithms continue to be optimized, deep learning technology is also expected to play a greater role in the protection of urban and rural cultural heritage.

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Abbreviations

The following abbreviations are used in this manuscript:

UAV	Unmanned Aerial Vehicle

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